autogluon_each_location

October 7, 2023

[29]:
```python
import pandas as pd
import numpy as np




import warnings
warnings.filterwarnings("ignore")

def fix_datetime(X, name):
    # Convert 'date_forecast' to datetime format and replace original column␣
↪with 'ds'
    X['ds'] = pd.to_datetime(X['date_forecast'])
    X.drop(columns=['date_forecast'], inplace=True, errors='ignore')
    X.sort_values(by='ds', inplace=True)
    X.set_index('ds', inplace=True)

    # Drop rows where the minute part of the time is not 0
    X = X[X.index.minute == 0]
    return X




def convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train):
    X_train_observed = fix_datetime(X_train_observed, "X_train_observed")
    X_train_estimated = fix_datetime(X_train_estimated, "X_train_estimated")
    X_test = fix_datetime(X_test, "X_test")


    X_train_observed["estimated_diff_hours"] = 0
    X_train_estimated["estimated_diff_hours"] = (X_train_estimated.index - pd.
↪to_datetime(X_train_estimated["date_calc"])).dt.total_seconds() / 3600
    X_test["estimated_diff_hours"] = (X_test.index - pd.
↪to_datetime(X_test["date_calc"])).dt.total_seconds() / 3600

    X_train_estimated["estimated_diff_hours"] =␣
↪X_train_estimated["estimated_diff_hours"].astype('int64')
    # the filled once will get dropped later anyways, when we drop y nans
```

```
    X_test["estimated_diff_hours"] = X_test["estimated_diff_hours"].fillna(-50).
 ↪astype('int64')


    X_train_estimated.drop(columns=['date_calc'], inplace=True)
    X_test.drop(columns=['date_calc'], inplace=True)

    y_train['ds'] = pd.to_datetime(y_train['time'])
    y_train.drop(columns=['time'], inplace=True)
    y_train.sort_values(by='ds', inplace=True)
    y_train.set_index('ds', inplace=True)

    return X_train_observed, X_train_estimated, X_test, y_train




def preprocess_data(X_train_observed, X_train_estimated, X_test, y_train,␣
 ↪location):
    # convert to datetime
    X_train_observed, X_train_estimated, X_test, y_train =␣
 ↪convert_to_datetime(X_train_observed, X_train_estimated, X_test, y_train)

    y_train["y"] = y_train["pv_measurement"].astype('float64')
    y_train.drop(columns=['pv_measurement'], inplace=True)
    X_train = pd.concat([X_train_observed, X_train_estimated])


    # clip all y values to 0 if negative
    y_train["y"] = y_train["y"].clip(lower=0)

    X_train = pd.merge(X_train, y_train, how="outer", left_index=True,␣
 ↪right_index=True)

    X_train["location"] = location
    X_test["location"] = location

    return X_train, X_test
# Define locations
locations = ['A', 'B', 'C']

X_trains = []
X_tests = []
# Loop through locations
for loc in locations:
    print(f"Processing location {loc}...")
    # Read target training data
```

```
    y_train = pd.read_parquet(f'{loc}/train_targets.parquet')

    # Read estimated training data and add location feature
    X_train_estimated = pd.read_parquet(f'{loc}/X_train_estimated.parquet')

    # Read observed training data and add location feature
    X_train_observed= pd.read_parquet(f'{loc}/X_train_observed.parquet')

    # Read estimated test data and add location feature
    X_test_estimated = pd.read_parquet(f'{loc}/X_test_estimated.parquet')

    # Preprocess data
    X_train, X_test = preprocess_data(X_train_observed, X_train_estimated,␣
↪X_test_estimated, y_train, loc)

    X_trains.append(X_train)
    X_tests.append(X_test)

# Concatenate all data and save to csv
X_train = pd.concat(X_trains)
X_test = pd.concat(X_tests)
```

```
Processing location A…
Processing location B…
Processing location C…
```

1 Feature enginering

[30]:
```
# temporary
X_train["hour"] = X_train.index.hour
X_train["weekday"] = X_train.index.weekday
# weekday or is_weekend
X_train["is_weekend"] = X_train["weekday"].apply(lambda x: 1 if x >= 5 else 0)

# drop weekday
#X_train.drop(columns=["weekday"], inplace=True)
X_train["month"] = X_train.index.month
X_train["year"] = X_train.index.year

X_test["hour"] = X_test.index.hour
X_test["weekday"] = X_test.index.weekday

# weekday or is_weekend
X_test["is_weekend"] = X_test["weekday"].apply(lambda x: 1 if x >= 5 else 0)

# drop weekday
#X_test.drop(columns=["weekday"], inplace=True)
```

```
X_test["month"] = X_test.index.month
X_test["year"] = X_test.index.year



to_drop = ["snow_drift:idx", "snow_density:kgm3"]

X_train.drop(columns=to_drop, inplace=True)
X_test.drop(columns=to_drop, inplace=True)

X_train.dropna(subset=['y'], inplace=True)
X_train.to_csv('X_train_raw.csv', index=True)
X_test.to_csv('X_test_raw.csv', index=True)
```

[31]:
```
# import autogluon.eda.auto as auto
# auto.dataset_overview(train_data=X_train, test_data=X_test, label="y",␣
↪sample=None)
```

[32]:
```
# auto.target_analysis(train_data=X_train, label="y")
```

2 Starting

[33]:
```
import os


# Get the last submission number
last_submission_number = int(max([int(filename.split('_')[1].split('.')[0]) for␣
↪filename in os.listdir('submissions') if "submission" in filename]))
print("Last submission number:", last_submission_number)
print("Now creating submission number:", last_submission_number + 1)

# Create the new filename
new_filename = f'submission_{last_submission_number + 1}'

hello = os.environ.get('HELLO')
if hello is not None:
    new_filename += f'_{hello}'

print("New filename:", new_filename)
```

```
Last submission number: 78
Now creating submission number: 79
New filename: submission_79
```

[34]:
```
from autogluon.tabular import TabularDataset, TabularPredictor
train_data = TabularDataset('X_train_raw.csv')
train_data.drop(columns=['ds'], inplace=True)
```

```
label = 'y'
metric = 'mean_absolute_error'
time_limit = 60
presets = 'best_quality'
```

```
Loaded data from: X_train_raw.csv | Columns = 52 / 52 | Rows = 93024 -> 93024
```

[35]:
```
predictors = [None, None, None]
```

[36]:
```
loc = "A"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
 ↪path=f"AutogluonModels/{new_filename}_{loc}").
 ↪fit(train_data[train_data["location"] == loc], time_limit=time_limit,␣
 ↪presets=presets)
predictors[0] = predictor
```

```
Warning: path already exists! This predictor may overwrite an existing
predictor! path="AutogluonModels/submission_79_A"
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_79_A/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.191-1 (2023-08-16)
Disk Space Avail:   102.14 GB / 105.09 GB (97.2%)
Train Data Rows:    34085
Train Data Columns: 50
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (5733.42, 0.0, 630.59471,
1165.90242)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    31398.19 MB
        Train Data (Original)  Memory Usage: 15.34 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
```

```
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
```

```
Training model for location A…
```

```
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…
        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 1): ['location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  5 | ['hour', 'weekday', 'is_weekend', 'month',
'year']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  4 | ['hour', 'weekday', 'month', 'year']
                ('int', ['bool']) :  2 | ['elevation:m', 'is_weekend']
        0.3s = Fit runtime
        49 features in original data used to generate 49 features in processed
data.
        Train Data (Processed) Memory Usage: 12.88 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.32s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
```

```
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.78s of the
59.68s of remaining time.
        -299.7062        = Validation score   (-mean_absolute_error)
        0.05s    = Training   runtime
        1.69s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 37.95s of the
57.85s of remaining time.
        -300.7424        = Validation score   (-mean_absolute_error)
        0.05s    = Training   runtime
        1.68s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 36.12s of the
56.02s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -165.3939        = Validation score   (-mean_absolute_error)
        30.87s   = Training   runtime
        21.58s   = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.68s of the
17.97s of remaining time.
        -165.3939        = Validation score   (-mean_absolute_error)
        0.3s     = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 17.65s of the
17.63s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -167.3696        = Validation score   (-mean_absolute_error)
        11.57s   = Training   runtime
        1.42s    = Validation runtime
```

```
Fitting model: LightGBM_BAG_L2 … Training model for up to 1.83s of the 1.82s
of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -176.7452        = Validation score   (-mean_absolute_error)
        2.62s    = Training   runtime
        0.16s    = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L3 … Training model for up to 59.68s of the
-4.08s of remaining time.
        -167.2361        = Validation score   (-mean_absolute_error)
        0.27s    = Training   runtime
        0.0s     = Validation runtime
AutoGluon training complete, total runtime = 64.4s … Best model:
"WeightedEnsemble_L2"
TabularPredictor saved. To load, use: predictor =
TabularPredictor.load("AutogluonModels/submission_79_A/")
```

[ ]:
```
loc = "B"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
 ↪path=f"AutogluonModels/{new_filename}_{loc}").
 ↪fit(train_data[train_data["location"] == loc], time_limit=time_limit,␣
 ↪presets=presets)
predictors[1] = predictor
```

```
Warning: path already exists! This predictor may overwrite an existing
predictor! path="AutogluonModels/submission_79_B"
Presets specified: ['best_quality']
Stack configuration (auto_stack=True): num_stack_levels=1, num_bag_folds=8,
num_bag_sets=20
Beginning AutoGluon training … Time limit = 60s
AutoGluon will save models to "AutogluonModels/submission_79_B/"
AutoGluon Version:  0.8.2
Python Version:     3.10.12
Operating System:   Linux
Platform Machine:   x86_64
Platform Version:   #1 SMP Debian 5.10.191-1 (2023-08-16)
Disk Space Avail:   102.13 GB / 105.09 GB (97.2%)
Train Data Rows:    32844
Train Data Columns: 50
Label Column: y
Preprocessing data …
AutoGluon infers your prediction problem is: 'regression' (because dtype of
label-column == float and many unique label-values observed).
        Label info (max, min, mean, stddev): (1152.3, -0.0, 96.82478, 193.94649)
        If 'regression' is not the correct problem_type, please manually specify
the problem_type parameter during predictor init (You may specify problem_type
```

```
as one of: ['binary', 'multiclass', 'regression'])
Using Feature Generators to preprocess the data …
Fitting AutoMLPipelineFeatureGenerator…
        Available Memory:                    31161.25 MB
        Train Data (Original)  Memory Usage: 14.78 MB (0.0% of available memory)
        Inferring data type of each feature based on column values. Set
feature_metadata_in to manually specify special dtypes of the features.
        Stage 1 Generators:
                Fitting AsTypeFeatureGenerator…
                        Note: Converting 2 features to boolean dtype as they
only contain 2 unique values.
        Stage 2 Generators:
                Fitting FillNaFeatureGenerator…
        Stage 3 Generators:
                Fitting IdentityFeatureGenerator…
        Stage 4 Generators:
                Fitting DropUniqueFeatureGenerator…

Training model for location B…

        Stage 5 Generators:
                Fitting DropDuplicatesFeatureGenerator…
        Useless Original Features (Count: 1): ['location']
                These features carry no predictive signal and should be manually
investigated.
                This is typically a feature which has the same value for all
rows.
                These features do not need to be present at inference time.
        Types of features in original data (raw dtype, special dtypes):
                ('float', []) : 44 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])   :  5 | ['hour', 'weekday', 'is_weekend', 'month',
'year']
        Types of features in processed data (raw dtype, special dtypes):
                ('float', [])     : 43 | ['absolute_humidity_2m:gm3',
'air_density_2m:kgm3', 'ceiling_height_agl:m', 'clear_sky_energy_1h:J',
'clear_sky_rad:W', …]
                ('int', [])       :  4 | ['hour', 'weekday', 'month', 'year']
                ('int', ['bool']) :  2 | ['elevation:m', 'is_weekend']
        0.2s = Fit runtime
        49 features in original data used to generate 49 features in processed
data.
        Train Data (Processed) Memory Usage: 12.42 MB (0.0% of available memory)
Data preprocessing and feature engineering runtime = 0.26s …
AutoGluon will gauge predictive performance using evaluation metric:
'mean_absolute_error'
        This metric's sign has been flipped to adhere to being higher_is_better.
The metric score can be multiplied by -1 to get the metric value.
```

```
        To change this, specify the eval_metric parameter of Predictor()
User-specified model hyperparameters to be fit:
{
        'NN_TORCH': {},
        'GBM': [{'extra_trees': True, 'ag_args': {'name_suffix': 'XT'}}, {},
'GBMLarge'],
        'CAT': {},
        'XGB': {},
        'FASTAI': {},
        'RF': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'XT': [{'criterion': 'gini', 'ag_args': {'name_suffix': 'Gini',
'problem_types': ['binary', 'multiclass']}}, {'criterion': 'entropy', 'ag_args':
{'name_suffix': 'Entr', 'problem_types': ['binary', 'multiclass']}},
{'criterion': 'squared_error', 'ag_args': {'name_suffix': 'MSE',
'problem_types': ['regression', 'quantile']}}],
        'KNN': [{'weights': 'uniform', 'ag_args': {'name_suffix': 'Unif'}},
{'weights': 'distance', 'ag_args': {'name_suffix': 'Dist'}}],
}
AutoGluon will fit 2 stack levels (L1 to L2) …
Fitting 11 L1 models …
Fitting model: KNeighborsUnif_BAG_L1 … Training model for up to 39.82s of the
59.74s of remaining time.
        -56.8241         = Validation score   (-mean_absolute_error)
        0.06s    = Training   runtime
        1.64s    = Validation runtime
Fitting model: KNeighborsDist_BAG_L1 … Training model for up to 37.87s of the
57.79s of remaining time.
        -56.7721         = Validation score   (-mean_absolute_error)
        0.05s    = Training   runtime
        1.56s    = Validation runtime
Fitting model: LightGBMXT_BAG_L1 … Training model for up to 36.15s of the
56.07s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
        -27.8389         = Validation score   (-mean_absolute_error)
        31.82s   = Training   runtime
        21.92s   = Validation runtime
Completed 1/20 k-fold bagging repeats …
Fitting model: WeightedEnsemble_L2 … Training model for up to 59.74s of the
17.31s of remaining time.
        -27.8389         = Validation score   (-mean_absolute_error)
        0.35s    = Training   runtime
        0.0s     = Validation runtime
Fitting 9 L2 models …
```

```
Fitting model: LightGBMXT_BAG_L2 … Training model for up to 16.94s of the
16.92s of remaining time.
        Fitting 8 child models (S1F1 - S1F8) | Fitting with
ParallelLocalFoldFittingStrategy
```

[ ]:
```
loc = "C"
print(f"Training model for location {loc}...")
predictor = TabularPredictor(label=label, eval_metric=metric,␣
 ↪path=f"AutogluonModels/{new_filename}_{loc}").
 ↪fit(train_data[train_data["location"] == loc], time_limit=time_limit,␣
 ↪presets=presets)
predictors[2] = predictor
```

3 Submit

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt

train_data_with_dates = TabularDataset('X_train_raw.csv')
train_data_with_dates["ds"] = pd.to_datetime(train_data_with_dates["ds"])

test_data = TabularDataset('X_test_raw.csv')
test_data["ds"] = pd.to_datetime(test_data["ds"])
#test_data
```

[ ]:
```
test_ids = TabularDataset('test.csv')
test_ids["time"] = pd.to_datetime(test_ids["time"])
# merge test_data with test_ids
test_data_merged = pd.merge(test_data, test_ids, how="inner", right_on=["time",␣
 ↪"location"], left_on=["ds", "location"])

#test_data_merged
```

[ ]:
```
# predict, grouped by location
predictions = []
location_map = {
    "A": 0,
    "B": 1,
    "C": 2
}
for loc, group in test_data.groupby('location'):
    i = location_map[loc]
    subset = test_data_merged[test_data_merged["location"] == loc].
 ↪reset_index(drop=True)
    #print(subset)
    pred = predictors[i].predict(subset)
    subset["prediction"] = pred
```

```
    predictions.append(subset)
```

[ ]:
```
# plot predictions for location A, in addition to train data for A
for loc, idx in location_map.items():
    fig, ax = plt.subplots(figsize=(20, 10))
    # plot train data
    train_data_with_dates[train_data_with_dates["location"]==loc].plot(x='ds',␣
 ↪y='y', ax=ax, label="train data")

    # plot predictions
    predictions[idx].plot(x='ds', y='prediction', ax=ax, label="predictions")

    # title
    ax.set_title(f"Predictions for location {loc}")
```

[ ]:
```
# concatenate predictions
submissions_df = pd.concat(predictions)
submissions_df = submissions_df[["id", "prediction"]]
submissions_df
```

[ ]:
```
# Save the submission DataFrame to submissions folder, create new name based on␣
 ↪last submission, format is submission_<last_submission_number + 1>.csv

# Save the submission
print(f"Saving submission to submissions/{new_filename}.csv")
submissions_df.to_csv(os.path.join('submissions', f"{new_filename}.csv"),␣
 ↪index=False)
```

[ ]:
```
# save this notebook to submissions folder
import subprocess
import os
subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
 ↪join('notebook_pdfs', f"{new_filename}.pdf"), "autogluon_each_location.
 ↪ipynb"])
```

[ ]:
```
# feature importance
# location="A"
# split_time = pd.Timestamp("2022-10-28 22:00:00")
# estimated = train_data_with_dates[train_data_with_dates["ds"] >= split_time]
# estimated = estimated[estimated["location"] == location]
# predictors[0].feature_importance(feature_stage="original", data=estimated,␣
 ↪time_limit=60*10)
```

[ ]:
```
# feature importance
# observed = train_data_with_dates[train_data_with_dates["ds"] < split_time]
# observed = observed[observed["location"] == location]
```

```
# predictor.feature_importance(feature_stage="original", data=observed,␣
↪time_limit=60*10)
```

```
[ ]: subprocess.run(["jupyter", "nbconvert", "--to", "pdf", "--output", os.path.
↪join('notebook_pdfs', f"{new_filename}_with_feature_importance.pdf"),␣
↪"autogluon_each_location.ipynb"])
```

```
[ ]: import subprocess

def execute_git_command(directory, command):
    """Execute a Git command in the specified directory."""
    try:
        result = subprocess.check_output(['git', '-C', directory] + command,␣
↪stderr=subprocess.STDOUT)
        return result.decode('utf-8').strip(), True
    except subprocess.CalledProcessError as e:
        print(f"Git command failed with message: {e.output.decode('utf-8').
↪strip()}")
        return e.output.decode('utf-8').strip(), False


git_repo_path = "."

execute_git_command(git_repo_path, ['config', 'user.email', 'you@example.com'])
execute_git_command(git_repo_path, ['config', 'user.name', 'Your Name'])

branch_name = new_filename

# add datetime to branch name
branch_name += f"_{pd.Timestamp.now().strftime('%Y-%m-%d_%H-%M-%S')}"

commit_msg = "run result"

execute_git_command(git_repo_path, ['checkout', '-b',branch_name])

# Navigate to your repo and commit changes
execute_git_command(git_repo_path, ['add', '.'])
execute_git_command(git_repo_path, ['commit', '-m',commit_msg])

# Push to remote
output, success = execute_git_command(git_repo_path, ['push',␣
↪'origin',branch_name])

# If the push fails, try setting an upstream branch and push again
if not success and 'upstream' in output:
    print("Attempting to set upstream and push again...")
```

```
    execute_git_command(git_repo_path, ['push', '--set-upstream',␣
↪'origin',branch_name])
    execute_git_command(git_repo_path, ['push', 'origin', branch_name])

execute_git_command(git_repo_path, ['checkout', 'main'])
```